Generative AI for Earth Observation, a Prospect

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***Abstract*—The huge amount of Earth Observation (EO) data from satellites and airborne platforms provides immense opportunities and new challenges for extracting real-time and precise information. Artificial Intelligence (AI) and Deep Learning (DL) have revolutionized how we analyze and process EO data. More specifically, Generative AI (GenAI) has already transformed many EO applications and this transformation is accelerating rapidly with the advancement of GenAI. Various generative models have been developed and applied to different EO applications, including synthetic data generation, gap filling, and super-resolution. Comprehensively understanding this new paradigm is necessary to envision the prospect of GenAI for different EO applications, its potential, limitations, and future impact. The main objective of this study is to provide a clearer image of the current state of GenAI in EO through a critical analysis of three different GenAI models, and to present a realistic forward-looking view on how GenAI could impact EO data processing in the future.**

Keywords— Artificial Intelligence, Deep Learning, Earth Observation, Generative AI, Generative Models

I. INTRODUCTION

Earth observation (EO) provides an immense tool for monitoring environment, disaster management, urban planning, and climate studies [1]. The advancements of Deep Learning (DL) and Artificial Intelligence (AI), particularly generative models, have greatly improved our ability to process, analyse, and generate synthetic EO data. These models are especially helpful for dealing with issues such as scarcity of high-quality annotated data or missing information. Generative AI (GenAI) provides useful solutions for EO studies by improving EO data generation techniques [2, 3].

With the rapid advancement of GenAI and the distinct impact that it has on EO applications, it is necessary to fully understand and envision the prospect of GenAI for EO. A clear understanding of GenAI for EO helps AI and EO researchers to study the capabilities and potential of these models for various applications, critically examine their limitations, and understand their impact on EO data processing pipelines. Moreover, such studies are essential for identifying the gaps, challenges and considerations of applying GenAI to EO data and reaching a trustworthy and domain-aware AI solutions for EO.

Traditional approaches for EO data generation and processing have mostly relied on physical models, statistical methods, and handcrafted feature extraction techniques. However, DL-based generative models can automatically learn relevant features from data without explicit programming, allowing them to adapt to complex patterns in EO imagery. Among various generative models, Variational autoencoders (VAEs) [4], Generative Adversarial Networks (GANs) [5, 6], and diffusion models [7] are prominent GenAI examples for synthetic EO data generation.

Conditional VAE (CVAE) is an extension of traditional VAEs by incorporating conditional variables into both encoding and decoding processes [4]. In EO applications, CVAEs facilitate the generation of synthetic satellite imagery conditioned on diverse parameters, including geographic coordinates, temporal factors, and meteorological variables.

StyleGAN2, is a GAN model that introduces a style-based generator to enable fine-grained control over image synthesis through disentangled representation learning [5]. StyleGAN2 facilitates the synthesis of diverse satellite imagery while maintaining precise control over domain-specific attributes.

Diffusion models constitute a recent advancement in generative modelling, operating through a principled formulation of the generative process as the reversal of a diffusion process [7]. The forward diffusion process systematically introduces Gaussian noise according to a predetermined schedule. The reverse generative process is parameterized by a neural network that iteratively denoises from pure noise to recover the original data distribution [7]. Diffusion models have gained attention for their capacity to generate photorealistic and structurally accurate satellite images, even under challenging multimodal scenarios [8].

In this study, three cutting-edge generative models, CVAE, StyleGAN2, and Improved Denoising Diffusion Probabilistic Models (Improved DDPM), are critically analyzed for their ability to generate synthetic EO data. The potentials and limitations of these models are discussed and later, a forward-looking view of the prospect on how GenAI could impact EO data processing in the future is provided.

II. GENERATIVE MODELS

In this section, the details of the generative models, including the CVAE, StyleGAN2, and Improved DDPM, are presented.

A. Conditional Variational Autoencoder (CVAE):

CVAE incorporates conditional variables into the encoding and decoding processes through a probabilistic mapping between input data and a structured latent space to generate data conditioned on auxiliary information [4, 9]. This probabilistic approach enables a flexible and uncertaintyaware image generation, particularly valuable for tasks where contextual conditions (e.g., location, weather) are crucial.

B. StyleGAN2:

StyleGAN2 [5] introduces a style-based generator architecture that provides disentangled control over various image synthesis attributes. In the EO domain, StyleGAN2 enables high-resolution image generation while maintaining fine control over structural and textural content relevant to geographic and atmospheric variations.

C. *Improved Denoising Diffusion Probabilistic Models (Improved DDPM):*

Improved Denoising Diffusion Probabilistic Models (Improved DDPM) [7] improves sampling speed and quality over earlier DDPMs. This model iteratively learns to reverse a Gaussian noise process, making it suitable for generating high-fidelity EO imagery. Diffusion models have recently shown strong promise for EO data synthesis, including in multimodal satellite data scenarios [10]. Forward pass gradually adds noise to data according to a variance schedule. Reverse pass gradually removes noise through an iterative denoising process to recover the original data distribution.

These models were selected to explore diverse generative mechanisms, from latent variable modeling (CVAE), adversarial learning (StyleGAN2), to denoising-based generation (Improved DDPM), in the context of remote sensing imagery.

III. EXPERIMENTAL RESULTS AND DISCUSSION

In this section we first introduce the datasets used for the experiments and then present and critically analyze the generated EO data from the generative models.

A. *Dataset*

Two datasets comprising multispectral data and Synthetic Aperture Radar (SAR) data are used in this study. EuroSAT dataset [11] provides RGB channels of Sentinel-2 images for ten different landcover classes in Europe. EuroSAT is a representative benchmark for evaluating generative models in EO field due to its diversity and availability. Fig. 1 shows an example of each landcover class represented in EuroSAT dataset.

In addition, TenGeoP-SARwv, introduced in [12], comprises 37560 SAR Sentinel-1 images in WV acquisition mode. These images represent ten distinct atmospheric and ocean-related physical phenomena. The ten classes are shown in Fig. 2 along with their corresponding class names.

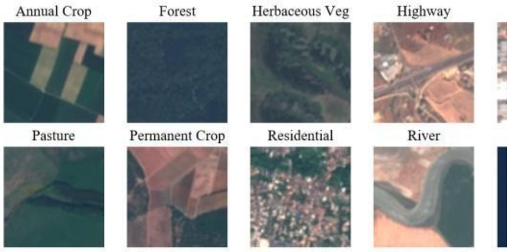

Fig. 1. EuroSAT dataset samples

B. *Experimental Results*

Fig. 3 demonstrates the data generated for various classes by each generative model. The first three rows compare the generated RGB images with the corresponding class from EuroSAT dataset by DDPM and CVAE models, respectively. Both models successfully preserved the overall features and colors of the original samples.

The images generated by the improved DDPM model have very sharp colors, compared to the original data, for instance see the industrial or Residential classes (5th and 8th columns respectively). Additionally, some inaccurately colored features can be detected in the images generated by DDPM. But the most prominent feature of the DDPM is the fine details and high quality of the generated samples.

The CVAE model was more successful in preserving the original colors of the data, but the generated images are blurrier and lack subtle details. For instance, comparing the same two classes (Industrial and Residential), CVAE correctly generates the expected features for each class but without the necessary details to match the spatial resolution and specific details of the original data. The blurriness of the generated images is a known problem in many VAE generative models.

The second three rows in Fig. 3 demonstrate the original SAR data from TenGeoP-SARwv dataset and the generated samples by improved DDPM and StyleGAN2 for each class.

Similar to the RGB image generation, the DDPM model produced sharp and intense features compared to the original data. The sharpness of the features in the DDPM generated images are visible in the more textured pattern of the generated samples (see the pure ocean waves and wind streaks classes on the 1st and 2nd rows of Fig. 3). The high quality and fine details of the generated samples is the most prominent feature of DDPM model.

StyleGAN2 has done a better job preserving the main properties and style of the original data. The generated samples illustrate a similar pattern and color intensity to the original images. However, StyleGAN2 generated images lack some subtle details in some classes, for example see the Low Wind Area class on the 7th row of Fig. 3.

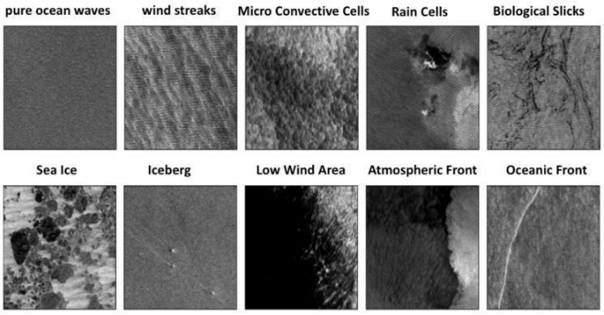

Fig. 2. TenGeoP-SARwv dataset samples

These results demonstrate the immense potential of the GenAI for EO applications and how it can generate highquality realistic synthetic EO data while preserving the original properties of the EO data.

Despite the promising results, the shortcomings and the caveats of GenAI should be considered and addressed. One of the worrying results from the generative models is the presence of some faulty images among the generated samples. Fig. 4 shows some examples of the faulty generated samples. These samples are generated by different models for different classes but lack the prominent features of the corresponding class. For instance, the first two images in Fig. 4 generated as the Sea Ice and Iceberg classes from TenGeoPSARwv dataset, respectively, but they do not represent the prominent features of these classes. Similarly, the rest of the samples in Fig. 4 show the faulty generated samples for the Sea/Lake, Residential, and Highway classes of the EuroSAT dataset. The presence of faulty generated images is a problem, especially for autonomous EO data generation tasks and should be considered while adopting GenAI models for EO applications.

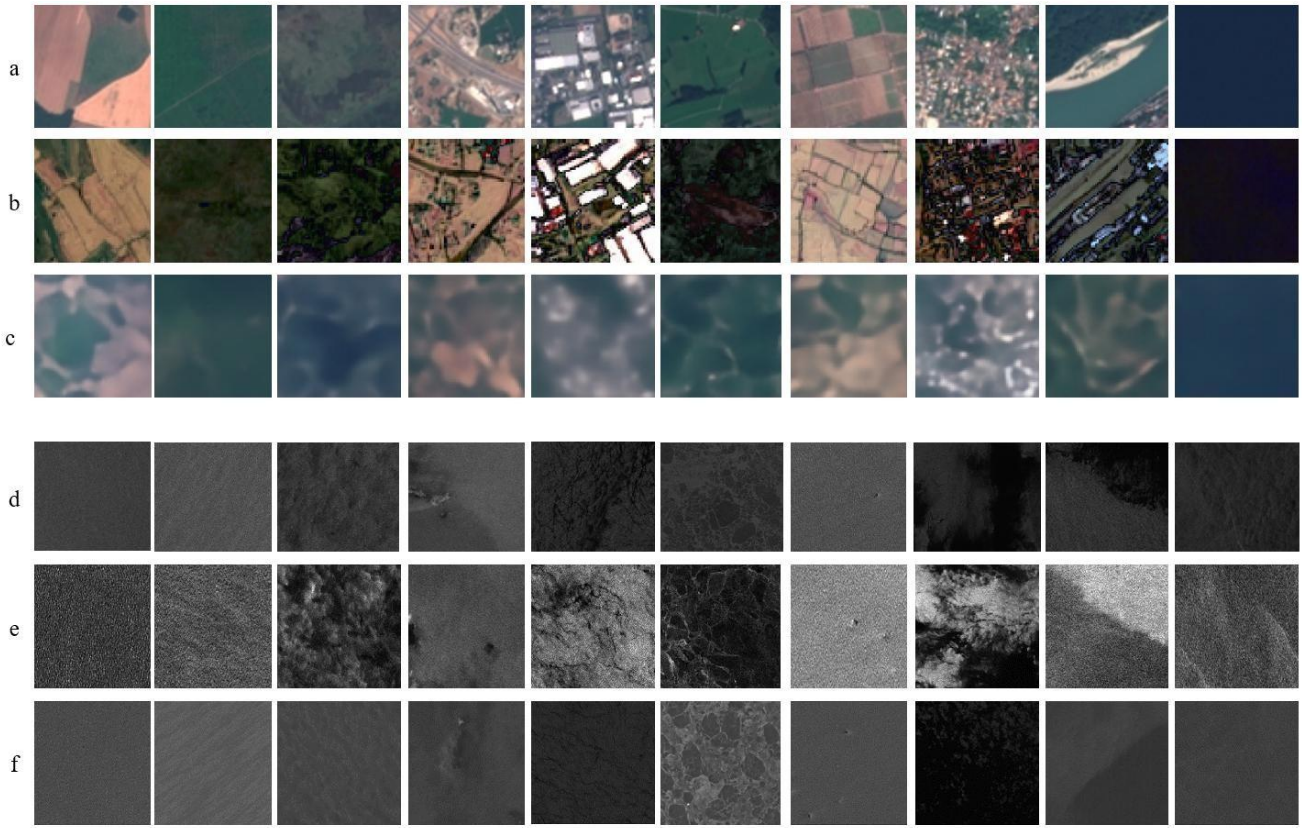

Fig. 3. Examples of the original and generated samples for each class in each dataset. a) original samples from EuroSAT dataset, b) generated RGB samples with the improved DDPM model, c) generated RGB samples with the CVAE model, d) original samples from TenGeoP-SARwv dataset, e) generated SAR samples with the improved DDPM model, and f) generated SAR samples with the StyleGAN2 model.

Fig. 4. Examples of faulty images generated by GenAI models. These samples fail to capture the key visual features of their intended classes, highlighting limitations in reliability that are critical to consider for EO tasks.

Another important limitation of the current generative models is the lack of physical properties. EO data are different from natural imagery and contain physical information derived from the physical world. Conventional generative models are unable to incorporate the physical properties of EO data. Lack of physical properties is more evident in SAR data, due to the peculiar physics of the SAR images. This is an important limitation that would restrict the practical applicability and adoptability of GenAI models for various EO applications and should be addressed. The ability of DL models for incorporating physical information and preserving physical properties of the original data has been studied in the literature [13, 14] and should be integrated into the generative models in the future studies [15].

While the promising generated samples in Fig. 3 show the huge potential of the GenAI models for EO applications, the faulty generated samples in Fig. 4 show the shortcomings of these models and the necessity of future studies to address these limitations.

IV. FUTURE PROSPECT

The results shown in this study and numerous other successful applications indicate the huge impact that GenAI would have on different EO domains. Further advancements of GenAI models will create more opportunities for various EO applications. However, these advancements will introduce novel challenges that should be considered and addressed.

Widespread use of synthetic EO data is one of the immediate impacts of GenAI in EO. With the advancement of GenAI, these models are able to generate massive realistic synthetic EO datasets that can be used for augmenting and diversifying training datasets and filling EO data gaps. Highquality and physically accurate synthetic data will be transformative for underrepresented data, such as extreme weather data or remote inaccessible regions.

Another immediate impact will be cross-sensor translation and data fusion. GenAI models will be able to generate synthetic data from another EO data type (e.g., generating synthetic SAR data from multispectral data), as well as harmonizing diverse EO data from different sensors to create multi-sensor harmonized EO datasets. Further advancements in this area can lead to super resolving lowresolution EO data and generating very high resolution EO datasets. Moreover, physics-aware GenAI will generate EO data with accurate physical properties. The physical properties in synthetic EO data are necessary for many EO applications, including Interferometric SAR (InSAR).

GenAI can provide more accessible and personalized EO products. Integration of Large Language Models (LLM) with vison models will enable nonexperts (e.g., farmers, urban planners, and decision makers) to input queries and receive personalized AI generated EO productions for their needs.

This will facilitate employing EO for diverse applications and expanding applicability of EO for everyday life applications.

In a larger scale, GenAI is essential for creating digital twins of Earth where researchers can simulate new scenarios at unprecedented spatial-temporal resolution. These models can be used for climate forecasting, ecosystem monitoring, and proactive disaster management.

GenAI models can also be deployed directly on EO satellites for real-time on-the-edge processing of the acquired data. It will enable improved data correction, data compression, and real-time data processing for disaster management.

Additionally, GenAI will be used in EO sensor design, especially for optimizing sensor parameters and simulating new EO data types for specific goals. These AI generated data will enable researchers to assess various novel EO sensors for diverse applications and lead to specialized novel EO sensors.

However, these advancements will also introduce new challenges. There are several concerns regarding ethical use of AI generated EO data. There is a critical need to develop suitable regulations for GenAI, especially in sensitive applications, to ensure ethical use of AI and validation frameworks for distinguishing AI generated EO data.

V. CONCLUSIONS

Our main objective in this paper was to explore the potential and limitations of the advanced GenAI models for EO data and to provide a forward-looking image of how GenAI can impact and transform EO applications. To this end, we critically assessed the potential and limitations of three advanced GenAI models, including CVAE, StyleGAN2 and improved DDPM for synthetic EO image generation. Our experimental results show that these models can successfully generate EO images while preserving key characteristics of original data. The DDPM model excelled in generating highquality images with fine details but tend to produce overly sharp colors and intensified features compared to the original data. In contrast, the CVAE model better preserved the original color distributions but generated blurry images lacking fine details. StyleGAN2 demonstrated a balanced performance, maintaining the main properties and patterns of the original data while occasionally missing subtle details in certain classes.

While these results highlight the huge potential of the GenAI for EO applications, mainly for data augmentation and synthetic image generation, there are several important limitations that should be addressed in the future studies, including missing key class features in some of the generated samples, some faulty samples among the generated images, and lack of physical properties in the generated images.

Finally, a brief forward-looking perspective on the impact of GenAI on EO is presented. With the advancements of GenAI, EO data processing will change hugely. Several new opportunities and applications will be created that would enhance EO products and make them more applicable and accessible for everyday life applications. However, GenAI will also introduce novel challenges (e.g., ethical use of AI generated EO data) that should be considered and addressed. The main motivation behind this study was to understand these opportunities and challenges which is essential for coordinating the advances of GenAI for EO applications in terms of method development, domain understanding and policy frameworks.

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